CSE 256 FA24: NLP UCSD PA3:

Retrieval-Augmented Generation (RAG) (40 points)

The goal of this assignment is to gain hands-on experience with aspects of **Retrieval-Augmented Generation (RAG)**, with a focus on retrieval. You will use **LangChain**, a framework that simplifies integrating external knowledge into generation tasks by:

- Implementing various vector databases for efficient neural retrieval. You will use a vector database for storing our memories.
- Allowing seamless integration of pretrained text encoders, which you will access via HuggingFace models. You will use a text encoder to get text embeddings for storing in the vector database.

Data
You will build a retrieval system using the QMSum Dataset, a human-annotated benchmark designed for question answering on long meeting transcripts. The dataset includes over 230 meetings across multiple domains.

Release Date: November 6, 2024 | Due Date: November 18, 2024

IMPORTANT: After copying this notebook to your Google Drive along with the two data files, paste a link to your copy below. To create a publicly accessible link:

1. Click the *Share* button in the top-right corner.
2. Select "Get shareable link" and copy the link.

Link: https://drive.google.com/file/d/1WFO09dDkf7L1CxXtYfGIwHAGIsgRThFY/view?usp=sharing

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Notes:

Make sure to save the notebook as you go along.

Submission instructions are located at the bottom of the notebook.

```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
drive.mount('/content/drive')

```

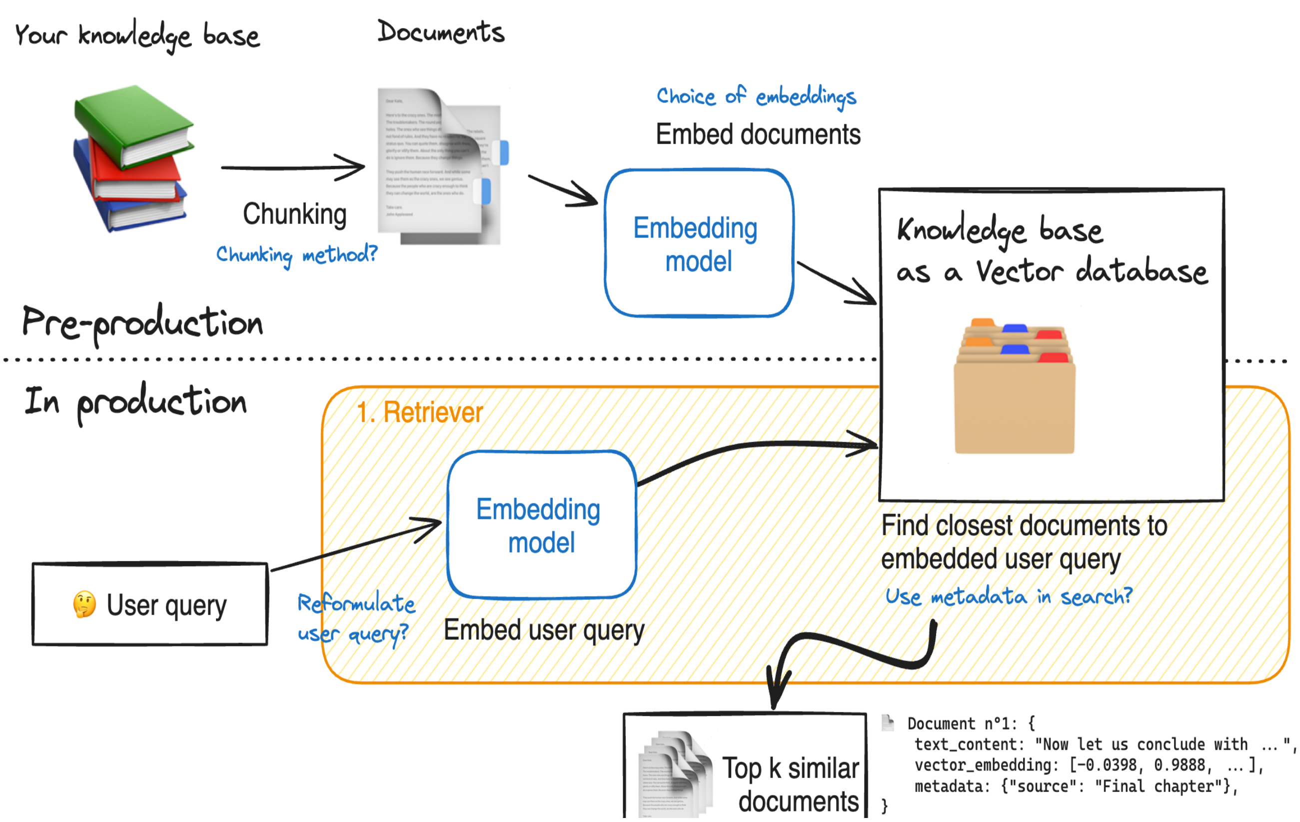
```
# TODO: Enter the foldername in your Drive where you have saved this notebook
# e.g. 'CSE156/assignments/PA3/'
FOLDERNAME = "Retrieval Augmented Generation"
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

# This is later used to use the IMDB reviews
%cd /content/drive/My\ Drive/$FOLDERNAME/
```

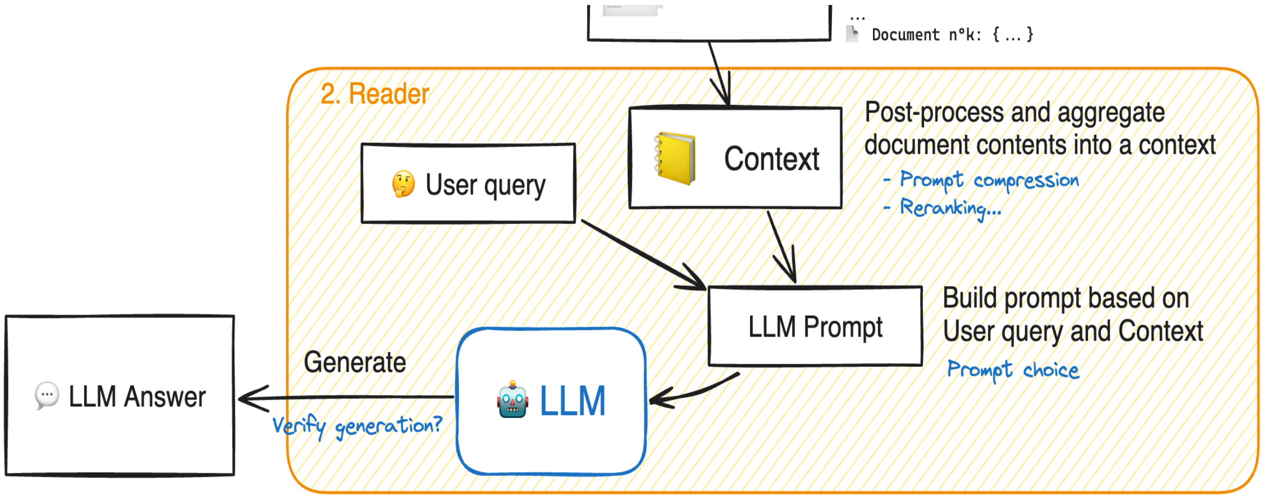
```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
/content/drive/My Drive/Retrieval Augmented Generation
```

RAG Workflow

Retrieval-Augmented Generation (RAG) systems involve several interconnected components. Below is a RAG workflow diagram from Hugging Face. Areas highlighted in blue indicate opportunities for system improvement.

In this assignment, we will focus on the ***Retriever** so the PA does not cover any processes starting from "2. Reader" and below.





First, install the required model dependancies.

```
pip install -q torch transformers langchain_chroma bitsandbytes langchain fais
```

```
from tqdm.notebook import tqdm
import pandas as pd
import os
import csv
import sys
import numpy as np
import time
import random
from typing import Optional, List, Tuple
import matplotlib.pyplot as plt
import textwrap
import torch


seed = 42
random.seed(seed)
np.random.seed(seed)
torch.manual_seed(seed)
torch.cuda.manual_seed_all(seed)
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

# Disable  huffingface tokenizers parallelism
os.environ["TOKENIZERS_PARALLELISM"] = "false"

```

Load the meetings dataset

```
from langchain.docstore.document import Document

def load_documents(doc_file):
    """
    Loads the document contents from the first file.

    :param doc_file: Path to the document file (document ID <TAB> document cont
    :return: A dictionary {document_id: document_contents}.
    """
    max_size = sys.maxsize
    csv.field_size_limit(max_size)


    documents = {}
    with open(doc_file, 'r', encoding='utf-8') as f:
        reader = csv.reader(f, delimiter='\t')
        for row in reader:
            if len(row)==0: continue
            doc_id, content = row
            documents[doc_id] = content
    return documents


docs =  [] #
doc_file = '/content/drive/My Drive/{}/meetings.tsv'.format(FOLDERNAME)
documents = load_documents(doc_file)

for doc_id in documents:
    doc = Document(page_content=documents[doc_id])
    metadata = {'source': doc_id}
    doc.metadata = metadata
    docs.append(doc)

print(f"Total meetings (docs):  {len(documents)}")

```

```
Total meetings (docs):  230
```

Retriever - Building the retriever 🗂️

The **retriever functions like a search engine**: given a user query, it returns relevant documents from the knowledge base.

These documents are then used by the Reader model to generate an answer. In this assignment

These documents are then used by the Reader model to generate an answer. In this assignment, however, we are only focusing on the retriever, not the Reader model.

Our goal: Given a user question, find the most relevant documents from the knowledge base.

Key parameters:

- `top_k`: The number of documents to retrieve. Increasing `top_k` can improve the chances of retrieving relevant content.
- `chunk size`: The length of each document. While this can vary, avoid overly long documents, as too many tokens can overwhelm most reader models.

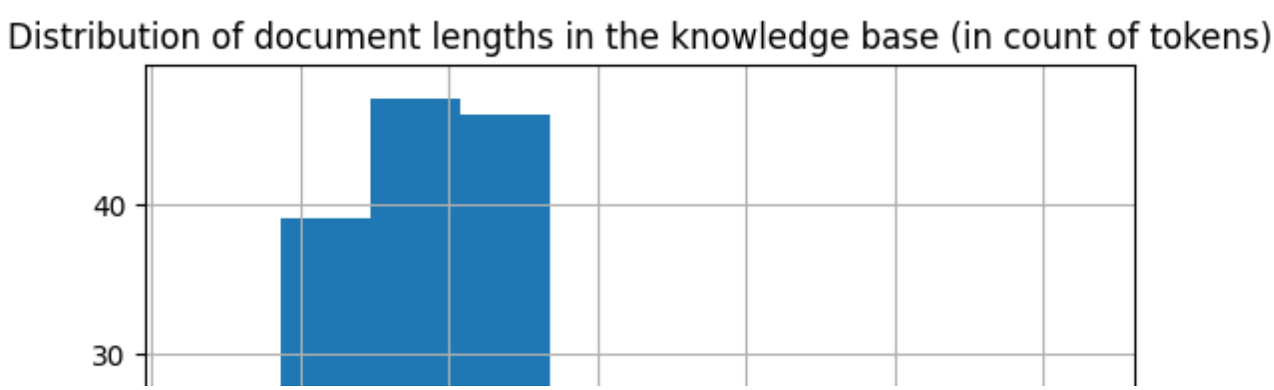
Langchain **offers a huge variety of options for vector databases and allows us to keep document metadata throughout the processing**.

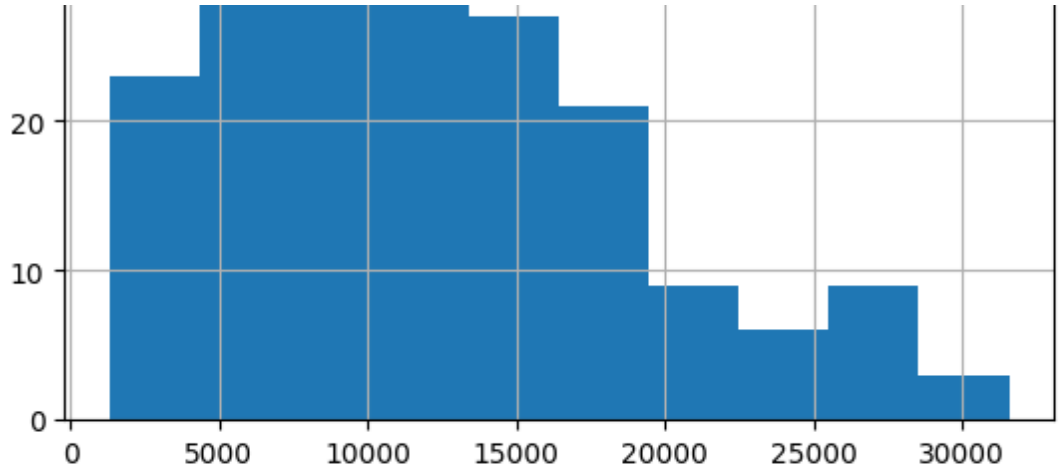
1. Specify an Embedding Model and Visualize Document Lengths

```
EMBEDDING_MODEL_NAME = "thenlper/gte-small"

from sentence_transformers import SentenceTransformer

print(
    f"Model's maximum sequence length: {SentenceTransformer(EMBEDDING_MODEL_NAM
)

from transformers import AutoTokenizer

tokenizer = AutoTokenizer.from_pretrained(EMBEDDING_MODEL_NAME)
lengths = [len(tokenizer.encode(doc.page_content)) for doc in tqdm(docs)]

# Plot the distribution of document lengths, counted as the number of tokens
fig = pd.Series(lengths).hist()
plt.title("Distribution of document lengths in the knowledge base (in count of
plt.show()
```

```
Model's maximum sequence length: 512
```

100% 230/230 [00:21<00:00, 14.35it/s]





2. Split the Documents into Chunks

The documents (meeting transcripts) are very long—some up to 30,000 tokens! To make retrieval effective, we'll **split each document into smaller, semantically meaningful chunks**. These chunks will serve as the snippets the retriever compares to the query, returning the `top_k` most relevant ones.

Objective: Create Semantically Relevant Snippets

Chunks should be long enough to capture complete ideas but not so lengthy that they lose focus.

We will use Langchain's implementation of recursive chunking with `RecursiveCharacterTextSplitter`.

- Parameter `chunk_size` controls the length of individual chunks: this length is counted by default as the number of characters in the chunk.
- Parameter `chunk_overlap` lets adjacent chunks get a bit of overlap on each other. This reduces the probability that an idea could be cut in half by the split between two adjacent chunks.

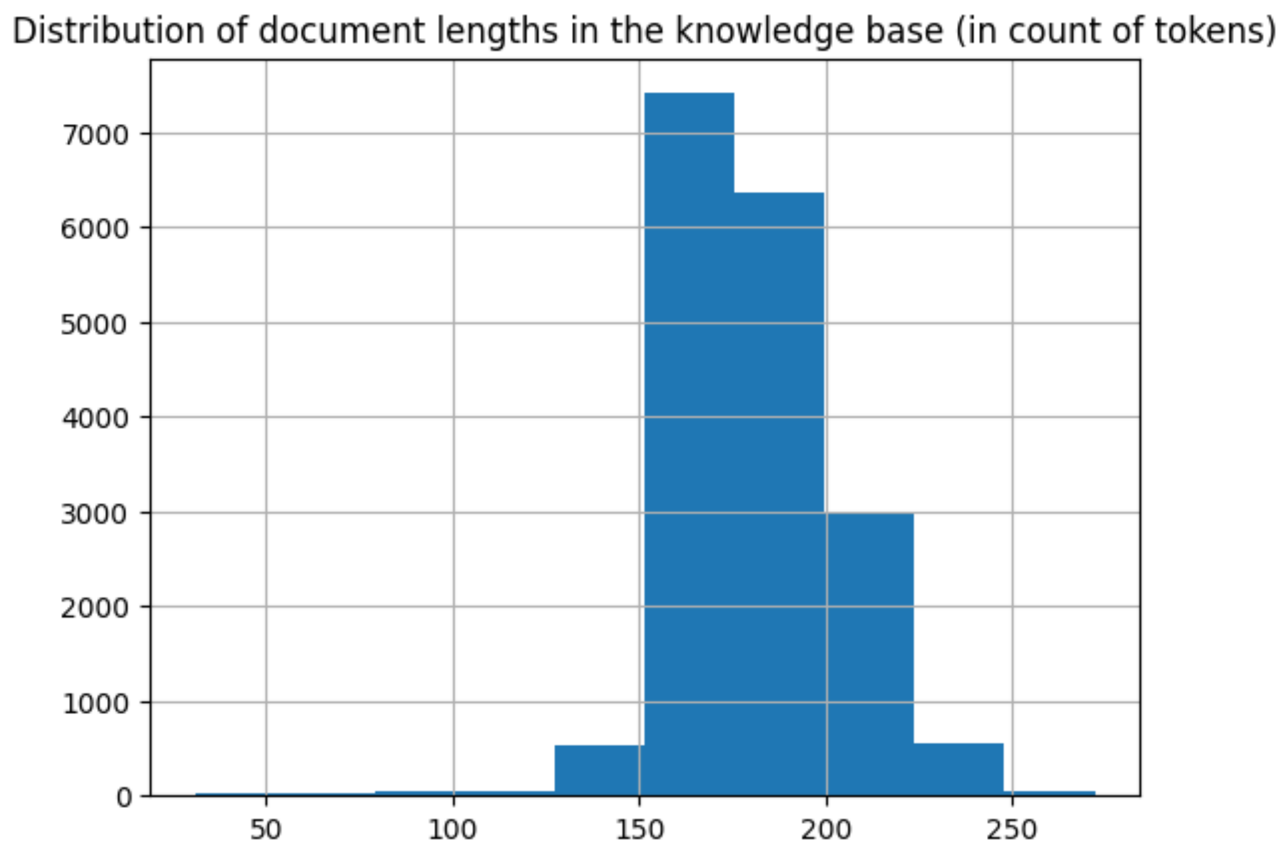
From the produced plot below, you can see that now the chunk length distribution looks better!

```
from langchain.text_splitter import RecursiveCharacterTextSplitter

text_splitter = RecursiveCharacterTextSplitter(
    chunk_size = 768,
    chunk_overlap = 128,
)

doc_snippets = text_splitter.split_documents(docs)
```

```
print(f"Total {len(doc_snippets)} snippets to be stored in our vector store.")

lengths = [len(tokenizer.encode(doc.page_content)) for doc in tqdm(doc_snippets

# Plot the distribution of document snippet lengths, counted as the number of t
fig = pd.Series(lengths).hist()
plt.title("Distribution of document lengths in the knowledge base (in count of
plt.show()
```

```
Total 18070 snippets to be stored in our vector store.
```

100% 18070/18070 [00:24<00:00, 1641.50it/s]



3. Build the Vector Database

To enable retrieval, we need to compute embeddings for all chunks in our knowledge base. These embeddings will then be stored in a vector database.

How Retrieval Works

A query is embedded using an embedding model and a similarity search finds the closest matching chunks in the vector database.

The following cell builds the vector database consisting of all chunks in our knowledge base.

```
from langchain_huggingface import HuggingFaceEmbeddings
from langchain.vectorstores import FAISS
from langchain_community.vectorstores.utils import DistanceStrategy

# Automatically set the device to 'cuda' if available, otherwise use 'cpu'
device = "cuda" if torch.cuda.is_available() else "cpu"
print(f"Found device: {device}")


embedding_model = HuggingFaceEmbeddings(
    model_name=EMBEDDING_MODEL_NAME,
    multi_process=True,
    model_kwargs={"device": device},
    encode_kwargs={"normalize_embeddings": True},  # Set `True` for cosine sim
)

start_time = time.time()

KNOWLEDGE_VECTOR_DATABASE = FAISS.from_documents(
    doc_snippets, embedding_model, distance_strategy=DistanceStrategy.COSINE
)

end_time = time.time()

elapsed_time = (end_time - start_time)/60
print(f"Time taken: {elapsed_time} minutes")
```

```
Found device: cuda
Time taken: 1.503506076335907 minutes
```

4. Querying the Vector Database

Using LangChain’s vector database, the function `vector_database.similarity_search(query)` implements a Bi-Encoder (covered in class), independently encoding the query and each document into a single-vector representation, allowing document embeddings to be precomputed.

Let's define the Bi-Encoder ranking function and then use it on a sample query from the QMSum dataset.

```
## The function for ranking documents given a query:
def rank_documents_biencoder(user_query, top_k = 5):
    """
    Function for document ranking based on the query.

    :param query: The query to retrieve documents for.
```

```
    :param query: The query to retrieve documents for.
    :return: A list of document IDs ranked based on the query (mocked).
    """
    retrieved_docs = KNOWLEDGE_VECTOR_DATABASE.similarity_search(query=user_que
    ranked_list = []
    for i, doc in enumerate(retrieved_docs):
        ranked_list.append(retrieved_docs[i].metadata['source'])

    return ranked_list  # ranked document IDs.


user_query = "what did kirsty williams am say about her plan for quality assura
retrieved_docs = rank_documents_biencoder(user_query)

print("\n==================================Top-5 documents===================
print("\n\nRetrieved documents:", retrieved_docs)
print("\n=====================================================================\n
```

```
==================================Top-5 documents============================

Retrieved documents: ['doc_211', 'doc_2', 'doc_43', 'doc_160', 'doc_43']

====================================================================
```

5. Implementation of ColBERT as a Reranker for a Bi-Encoder (35 points)

The Bi-Encoder's ranking for the sample query is not optimal: the ground truth document is not ranked at position 1, instead the document ID, **doc_211** is ranked at position 1. To determine the correct document ID for this query, refer to the `questions_answers.tsv` file.

In this task, you will implement the ColBERT approach by Khattab and Zaharia. We'll use a simplified version of ColBERT, focusing on the following key steps:

1. Retrieve the top (K = 15) documents for query (q) using the Bi-Encoder.
2. Re-rank these top (K = 15) documents using ColBERT's fine-grained interaction scoring. This will involve:
    - Using frozen BERT embeddings from a HuggingFace BERT model (no training is required, thus our version is not expected to work as well as full-fledged ColBERT).
    - Calculating scores based on fine-grained token-level interactions between the query and each document.
3. Implement the method `rank_documents_finegrained_interactions()` to perform this re-ranking.
    - Test your method on the same query as in the cell from #4 above.

- Test your method on the same query as in the cell from #4 above.
- Print out the entire re-ranked document list of 5 document IDs, as done in #4 above (the code below does it for you)

4. Ensure that your ColBERT implementation ranks the correct document at position 1 for the sample query.

Note: Since the same document is divided into multiple chunks that retain the original document ID, you may see the same document ID appear multiple times in your top_k results. However, each instance refers to a different chunk of the document's content.

Note2: For this PA we are not focused on query latency, just the late interactions part in the ColBERT approach. Thus, we don't have to pre-compute document matrix representations for ColBERT.

Note3:: Both the bi-encoder and the ColBERT used in this PA are not trained for retrieval and their performance is therefore not SOTA. What we are doing is ***zero-shot transfer for retrieval from BERT***. For SOTA retrieval performance both have to be trained on data of the form (q, doc+, docs-). For this PA, it is best to leave the setup as is for grading purposes. But you can certainly explore for your own purposes.

```
import torch
import torch.nn.functional as F
from transformers import AutoTokenizer, AutoModel


# Load tokenizer and model BERT from HuggingFace
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
model = AutoModel.from_pretrained("bert-base-uncased")


def rank_documents_finegrained_interactions(user_query, shortlist = 15, top_k=5

    """
    Rerank the top-K=15 retrieved documents from Bi-encoder using fine-grained
    and return the top_k=5 most similar documents.

    Args:
    - user_query (str): The user query string.
    - shortlist (list): Number of documents in the longer short list
    - top_k (int): Number of top reranked documents to return.

    Returns:
    - ranked_list of document IDs.
    """

    retrieved_docs = KNOWLEDGE_VECTOR_DATABASE.similarity_search(query=user_que
```

```
    # Tokenize the user query
    query_inputs = tokenizer(user_query, return_tensors='pt', truncation=True,

    # Get query token embeddings from BERT
    with torch.no_grad():
        query_embeddings = model(**query_inputs).last_hidden_state  # Shape: (1

    ranked_list = []

    ### YOUR CODE HERE
    #query_length = query_embeddings.shape[1]
    #hidden_dim = query_embeddings.shape[2]
    similarities = torch.zeros((shortlist))

    with torch.no_grad():

      # Query: (1, Q_l, 768)
      # Document: (1, D_l, 768) -> T -> (1, 768, D_1)

      for i, doc in enumerate(retrieved_docs):
        doc_id = retrieved_docs[i].metadata['source']
        doc_text = retrieved_docs[i].page_content

        # Get tokens for document text
        doc_inputs = tokenizer(doc_text, return_tensors='pt', truncation=True,

        # Get embeddings for document text
        doc_embeddings = model(**doc_inputs).last_hidden_state

        # Compute similarity matrix (1, Q_l, D_l)
        sim_matrix = torch.matmul(query_embeddings, doc_embeddings.transpose(1,

        # Compute max similarity for each query token, (1, Q_l)
        max_sims, _ = torch.max(sim_matrix, dim=2)

        sum_similarities = torch.sum(max_sims) # scalar
        similarities[i] = sum_similarities

    sorted_indices = torch.argsort(similarities, descending=True)

    for i in range(top_k):
      ranked_list.append(retrieved_docs[sorted_indices[i]].metadata['source'])

    return ranked_list  # ranked document IDs


user_query = "what did kirsty williams am say about her plan for quality assura
retrieved_docs = rank_documents_finegrained_interactions(user_query)
```

```
print("\n==================================Top-5 documents====================
print("\n\nRetrieved documents:", retrieved_docs)
print("\n====================================================================\r
```

```
==================================Top-5 documents=============================

Retrieved documents: ['doc_2', 'doc_102', 'doc_2', 'doc_160', 'doc_160']

====================================================================
```

6. ColBERT Max vs. Mean Pooling for Relevance Scoring of Documents: (5 points)

ColBERT uses a form of **max pooling**, where each query term's contribution to the relevance score of a document is determined by its maximum similarity to any document term. One alternative approach is **mean pooling**, where each query term's contribution is calculated as the average similarity across all document terms.

Discuss the merits and potential limitations of using mean pooling versus max pooling in ColBERT. In your answer, consider how each approach might affect retrieval accuracy, sensitivity to specific token matches, interpretability, and anything you deem relevant. You are welcome to use an analysis of ColBERT's performance on the provided sample query in your discussion, but this is not required.

Explain here (<= 5 sentences) :

The choice between max and mean pooling affects how the similarities between query and documents are compressed. By taking the maximum similarity to all document terms, the model will be highly sensitive to individual token similarities while losing general similarity patterns. Inversely, mean pooling considers general patterns in similarity, and though more robust than max pooling, mean pooling may incorrectly label documents as dissimilar if the mean similarity is bounded by negative query-document token similarities. Therefore, whether max or mean pooling would be more accurate is dependent on the distribution of token similarities. One heuristic for choosing between these methods could be to inspect the cumulative mass function of edge case token similarities.

Submission Instructions

---

1. Click the Save button at the top of the Jupyter Notebook.
2. Select Runtime -> Run All. This will run all the cells in order, and will take several minutes.
3. Once you've rerun everything, save a PDF version of your notebook. Make sure all your code and answers are displayed in the pdf, it's okay if the provided codes get cut off because lines are not wrapped in code cells).
4. Look at the PDF file and make sure all your code and answers are there, displayed correctly. The PDF is the only thing your graders will see!
5. Submit your PDF on Gradescope.

7. (Optional) Full evaluation pipeline for your own exploration.

For this assignment, we only ask you to explore one sample query. Running on many queries is super slow without the right compute. If you have compute/and/or time to wait, below is a more complete evaluation setup that works with all the queries in QMSum dataset, and reports the `precision@k=5` metric.

Note: you need to remove the comment markers from the code below.

```

# def load_questions_answers(qa_file):
#     """
#     Loads the questions and corresponding ground truth document IDs.

#     :param qa_file: Path to the question-answer file (document ID <TAB> ques
#     :return: A list of tuples [(document_id, question, answer)].
#     """
#     qa_pairs = []
#     with open(qa_file, 'r', encoding='utf-8') as f:
#         reader = csv.reader(f, delimiter='\t')
#         for row in reader:
#             doc_id, question, answer = row
#             qa_pairs.append((doc_id, question, answer))

#     random.shuffle(qa_pairs)

#     return qa_pairs

# def precision_at_k(ground_truth, retrieved_docs, k):
#     """
#     Computes Precision at k for a single query.

#     :param ground_truth: The name of the ground truth document.
#     :param retrieved_docs: The list of document names returned by the model
#     :param k: The cutoff for computing Precision.
```

```
#     :return: Precision at k.
#     """
#     return 1 if ground_truth in retrieved_docs[:k] else 0
# def evaluate(doc_file, qa_file, ranking_fuction = None, k= 5):
#     """
#     Evaluate the retrieval system based on the documents and question-answer
#     :param doc_file: Path to the document file.
#     :param qa_file: Path to the question-answer file.
#     :param k: The cutoff for Precision@k.
#     """
#     # Load the QA pairs
#     qa_pairs = load_questions_answers(qa_file)
#     precision_scores = []
#     for doc_id, question, _ in qa_pairs:
#         retrieved_docs = ranking_fuction(question)
#         precision_scores.append(precision_at_k(doc_id, retrieved_docs, k))
#         avg_precision_at_k = sum(precision_scores) / len(precision_scores)
#         if len(precision_scores) %10==0:
#             print(f"After {len(precision_scores)} queries, Precision@{k}: {av
#     # Compute average Precision@k
#     avg_precision_at_k = sum(precision_scores) / len(precision_scores)
#     print(f"Precision@{k}: {avg_precision_at_k}")
# qa_file = 'questions_answers.tsv'  # document ID <TAB> question <TAB> answer
# start_time = time.time()
# evaluate(doc_file, qa_file,rank_documents_biencoder)
# end_time = time.time()
# elapsed_time = (end_time - start_time)/60
# print(f"Time taken: {elapsed_time} minutes")
```